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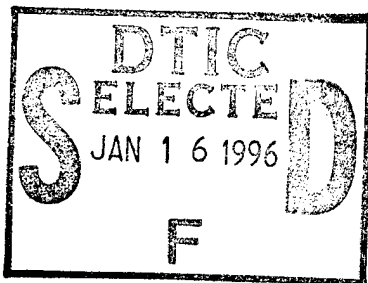
SMART COMPOSITE DAMAGE ASSESSMENT SYSTEM
BASED ON THE NEURAL NETWORK

by

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SMART COMPOSITE DAMAGE ASSESSMENT SYSTEM BASED ON THE
NEURAL NETWORK

Tao Yungang   Tao Baoqi

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ABSTRACT

This article introduces a new type of composite
material damage assessment system. The system in question
is composed of embedded optical fiber sensor arrays, shape
memory alloy wires, and Kohenen self-organizing neural
network processors. Material damage detection is realized
by embedded optical fiber sensor arrays. High speed neural
network parallel distribution processors composed of
TMS320C25 high speed parallel processors and IBM PC/386's
carry out simulations, realizing sensor output signal real
time processing. In conjunction with that, corresponding
control signals are produced to actuate shape memory alloy
(SMA) wires in order to change material stress
configurations and delay material destruction.

KEY WORDS Neural nets Composites Damage assessment

Chinese Library Classification No. V241.06, TP206.3

Compared to metallic materials, composites are much more
complicated in the areas of mechanical actions, destruction and
damage, and loss of effectiveness. For example, in impact
situations, the outer surfaces of composite materials are normal.
However, the inner damage can be very great. With regard to
there still being no effective means to carry out inspections of
existing defects, nondestructive inspection and monitoring of
materials is then even more difficult, thereby limiting the range
of applications of composite materials [1]. Smart composite
materials are nothing else than ones constructed of embedded
optical fiber sensor arrays and shape memory alloy wires under

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[t] Numbers in margins indicate foreign pagination.
Commas in numbers indicate decimals.

the control of processors. Shape memory alloy wires act as the mechanical properties of composite materials, making components alter. In smart composite materials, the processors used must handle optical fiber sensor output signals, and, in conjunction with that, produce the corresponding control signals to actuate memory alloys. However, sensors and actuation can be distributed within very large ranges. They can be composed from a few tens or more than a thousand dispersed elements. It is necessary to go through large amounts of calculations as well as spend a certain period of time. Artificial neural networks are capable of providing one integral parallel calculation structure. It is possible to carry out real time processing on multiple inputs and multiple outputs. In conjunction with that, training is gone through in order to learn correct logic. After completion of training, it is possible to make correct decisions with regard to input signals which have not been trained. This article opts for the use of Kohonen self-organizing neural networks in order to realize smart composite material processors. Signals are inputed from optical fiber sensors. Neural network output signals are shape memory alloy wire control signals, realizing smart composite material damage assessment. /1275

1 Self-Organizing Characteristic Projection Networks as Well as Their Improvement Learning Algorithms

1.1 Kohonen Self-Organizing Characteristic Projection Networks and Algorithms

Self-organizing characteristic projection principles can be summarized as: Assuming a statistical sample array $X = X(t) \in R^k$ as well as a set of different weighting vectors $\{W_j = W_j(t) \in R^k,\ j = 1, 2, \cdots, N\}, W_j$ takes a certain form of initialization. If, based on certain types of distance measurement $d(Z, W_j)$, Z is capable of carrying out comparisons with all the W_j at the instants t of each iteration in the sequence, then the W_j closest to distances X are nothing else than responses or matches associated with X.

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Note $W_c = W_c(t)$ that is,

$$W_c: d(X, W_c) \leqslant d(X, W_j), \ j = 1, 2, \cdots, N \qquad (1)$$

Considering correlation characteristics of regions, carry out adjustments with regard to Wc and weighting vectors in their vicinity facing toward directions approaching X. The remaining weighting vectors do not change. Then, different weighting vectors are capable of adjusting to different regions associated with mutual matches between input forms.

The structure of Kohonen self-organizing characteristic projection neural networks is as shown in Fig.1(a). It is a two layered network. Output nodal points are arranged on the output plane in order. Each output nodal point has a topological region. Each output nodal point and the other nodal points adjacent to it are connected to each other. This type of nodal point region is represented as shown in Fig 1(b). Its learning processes can be supervised or unsupervised. Normally,
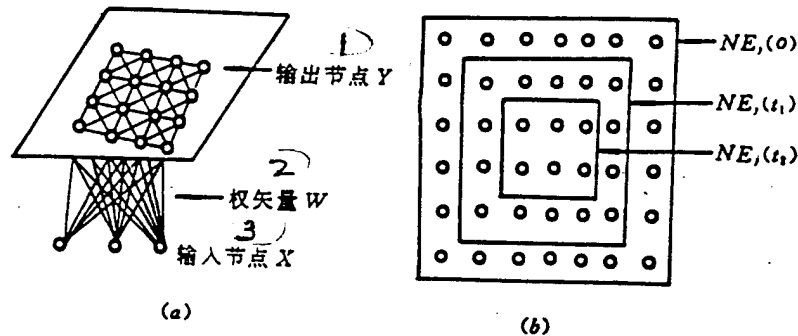

(a)   (b)

Fig.1 Kohonen Self-Organizing Characteristic Projection Network Structure

Key: (1) Output Nodal Point (2) Weighting Vector (3) Input Nodal Point

supervised networks are used in types of situations possessing
artificially defined clusters of modes--for example, used in
determining composite material damage locations. Nonsupervised
networks normally are appropriate for use in statistical analysis
situations possessing naturally formed clusters--for example, to
determine maximum strain values in composite materials. In
training periods, neural networks opt for the use of competitive
autoinstruction rules, giving each neural element in the network
a small random weighting value. Comparisons of weighting values
and the Euclidean distances between input vectors are gone
through in order to respond to special input modes, that is

$$\|X - W_c\| = \min \|X - W\| \tag{2}$$

Here, X and W respectively stand for inputs and weighting
vectors. W_c's are weighting vectors associated with victorious
elements. Only victorious elements alter their weighting values.
In conjunction with this, their position in the network is
determined. If victorious elements are located within the
expected clusters, this means that input modes and correct
classes are consistent. Going through increases in partial
inputs and weighting vector differential values causes the
weighting vectors of victorious elements to approach input
vectors. The learning rule is

$$W_c(t+1) = W_c(t) + a(t)[X(t) - W_c(t)] \tag{3}$$

In this, a(t) is learning rates as time periods are reduced
(0<a(t)<1). If victorious elements are located outside the
expected clusters, this means that input modes fall into the
wrong classifications. Through reducing partial differential
values, weighting vectors associated with victorious elements are
far removed from input vectors. The learning rule is

$$W_c(t+1) = W_c(t) - a(t)[X(t) - W_c(t)] \qquad (4)$$

Starting out from the network viewpoint, training processes can be recognized to be processes of victorious elements moving around networks. After going through adequate training, each victorious element associated with single individual input modes are stabilized within the expected clusters. Moreover, speaking in terms of relative input collections, weighting vectors associated with entire networks are located at maxima. What is inadequate is that training periods associated with standard learning algorithms require long periods of time--in particular, when expected clusters are very numerous and initial probabilities of specially selected input modes matching expected clusters are relatively small.

1.2   Improved Learning Algorithms

Research on nerve cells clearly shows that they possess a type of feedback structure associated with mutual interactions between the neural cells. Adjacent cells stimulate each other. Relatively distant cells mutually inhibit. Those even farther away again have weak stimulation effects. In self-organizing characteristic projection neural networks, the various nodal points responding within the nodal point vicinity possess the same or similar characteristics. That being the case, however, these nodal point do not necessarily belong to the same class. In particular, when input mode types are very numerous, adjustments with regard to nodal point weightings should reflect even more differences in the classifications [2]. To this end, option is made for the use of improved algorithms associated with two types of gain factors of different magnitudes

$$W_j(t+1) = \begin{cases} W_j(t) + a_1(t)[X(t) - W_j(t)]; & j = c \\ W_j(t) + a_2(t)[X(t) - W_j(t)]; & j \in NE_c(t), \ j \neq c \qquad (5) \\ W_j(t); \end{cases}$$

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In this, $a_1(t)$ and $a_2(t)$ are respectively the different gain factors. $a_1(t)$ guarantees the stable adjustment of responding nodal points. In initial adjustment phases, $a_1(t)<a_2(t)$ causes adjustments to be capable of rapid execution. In fine adjustment phases, $a_1(t)>a_2(t)$ is in order to maintain the characteristics of the different classes.

2 Damage Assessment Systems Based on SOM Networks

When carrying out damage assessments, it is hoped to be able to rapidly determine the location and severity of damage appearing in such mechanical structures as the wings of aircraft, and, in conjunction with that, to carry out control. Option is made for the use of an experimental system such as the one shown in Fig.2. Composite material experimental items are manufactured from plates of glass fiber composite material and installed on a rack capable of changing into multiple types of support forms. 10 optical fibers each are embedded in equal intervals along the x and y axes of a 1mx1m area in the middle of the plate. Four elements each of shape memory alloy wires are embedded in two planes at equal 1.5mm heights from the central surface. In this, the dimensions of each grid are $0.1x0.1m^2$. Positions are matched and parallel to optical fibers.

As far as light coming from laser diodes is concerned, it passes through a radial coupling device coupling two dimensional optical fiber strain sensor arrays. The light strength of the output of each optical fiber sensor is a function of the strain distribution on its optical channel. Damage due to fatigue or given rise to by external causes will bring about physical displacement of material. In conjunction with this, it will lead to a type of special strain distribution related to damaged locations. Embedded optical fiber sensor arrays are capable of doing test measurements of strain distributions. In conjunction with this, an optical strength distribution corresponding to them

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is outputed. This goes through photoelectric convertor
connections and acts as neural network processor input.
Supervised Kohonen neural networks which have gone through
training before the fact are capable of determining the location
and severity of damage which appears. Damage points are shown on
the display screens of 386 computers. Their location on display
screens and their locations on wings correspond to each other.
At the same time, corresponding actuation signals are produced.
Automatically altering the configuration of a few memory alloy
wires among them causes damaged locations to be placed into a
compression stress configuration in order to delay material
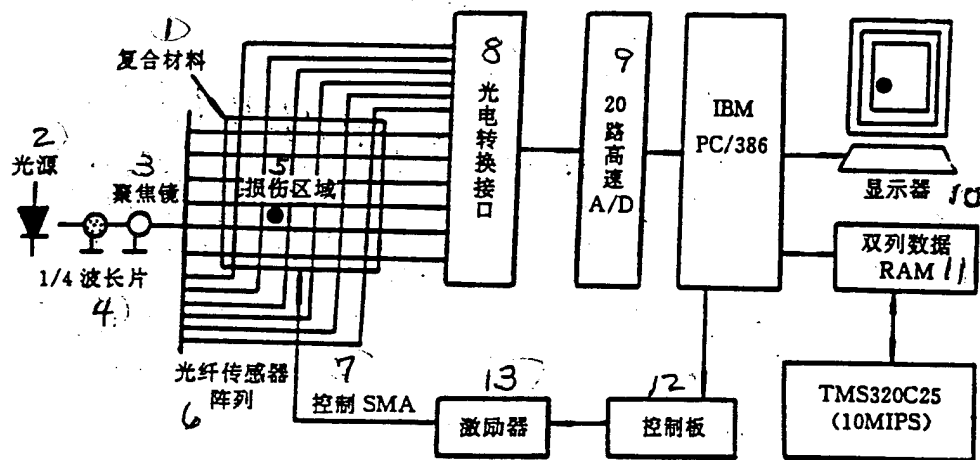destruction.

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Fig.2 Damage Assessment System Based on SOM Network

Key: (1) Composite Material (2) Light Source (3) Focusing
Reflector (4) 1/4 Wave Length Plate (5) Damage Region (6)
Optical Fiber Sensor Array (7) Control (8) Photoelectric
Convertor Connections (9) 20 Circuit High Speed A/D (10)
Display Device (11) Biserial Data RAM (12) Control Panel
(13) Actuation Device

As far as neural networks are concerned, high speed parallel distribution processors composed of TMS320C25 high speed parallel processors and IBM PC/386's conduct simulations. The TMS320C25 internal structure is 32 bit. Each second, it is possible to carry out more than 10 million commands (10MIPS), possessing capabilities for synchronous operations between multiple processors. In conjunction with this, there are memory storage devices to support sharing situations associated with multiple processors. Between them and IBM PC/386's, option is made for the use of dual terminal port RAM technology and biserial data storage areas. In this way, it makes main computers and high speed parallel processed data from machines go through rational and ingenious software designs to make data divide up into two parts, using two processors for respective handling. Biserial memory storage areas are capable of making the advantages associated with TMS320C25 high speed processing data come into full play. However, they let PC machines and slow speed I/O equipment, which have relatively strong main line control capabilities, carry out data exchange and transmission. For example, with regard to 20 signal circuits coming from photoelectric connections, they are gathered by 20 circuit 12 bit 200KHz A/D convertors associated with PC control. The data acts as neural network input. However, various types of operations associated with the completion of neural network processing, by contrast, are completed by TMS320C25's. Finally, control signals actuating shape memory alloy wires are sent out by PC's through measurement and control panels. In conjunction with this, corresponding damage locations are shown on PC display screens.

3 Simulation Experiments

As far as the 20 optical fibers embedded in composite material test panels and the 64(8x8) neural element clusters positioned there are concerned, each neural element cluster stands for one damage spot in the neural network. Corresponding

to 64 individual localized damage locations, 64 training data sets are prepared. Each set among them is an output strain value representing optical fiber array sensors. Neural network processors are 20 input 64 output systems. During training, each set of data is randomly sent into the neural network. When training begins, the learning rate is taken as 0.05. Going through 2048 iterative substitutions, the learning rate drops to 0.04. At the beginning, there is no input matching to expected clusters. Here, due to initial weighting values being random, after going through 900 iterative substitutions, matched input data rapidly increases. After going through 2048 iterative substitutions, all the input data is matched to expected clusters. At this time, weighting values are optimal. Training is also then completed.

This article only carried out simulations on situations where there was one damage location. However, this type of damage assessment method, in the same way, is capable of being used in detection and measurement of multiple damage sites. In a certain situation where multiple damage sites are detected--for each individual type of strain distribution mode--multiple cluster Kohonen neural networks will point out damage locations. Reference [3] carried out calculation and analysis tests.

REFERENCES

1 Grossman B, Gao X. Thursby M. Composite damage assessment employing an optical neural network processor and an embedded fiberoptic sensor array, SPIE fiber optic smart structure and skin 1991; 1588(4): 64—75
2 禹宏涛, 蔡德钧. 一种用于图象编码的神经网络及其改进算法. 信号处理, 1992: (9): 176—182
3 Grossman B, Caimi F. Smart structures and fiber optic sensor research at florida institute of technology—1990 SPIE Fiber optic smart structures and skins, 1990; 1370(4): 69—83

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